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How Siemens Democratized Artificial Intelligence

Many firms aspire to generate business value with artificial intelligence (AI) but struggle to move beyond pilots and prototypes. Based on an in-depth case study, we describe how Siemens has leveraged AI democratization to identify, realize and scale AI use cases by integrating the unique skills of domain experts, data scientists and IT professionals. From the lessons learned at Siemens, we provide recommendations for building this organizational capability and effectively addressing the challenges of adopting the latest AI technologies.[1,2]

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Artificial Intelligence Growth Requires Broad Organizational Involvement

The steep rise of artificial intelligence (AI) has spawned new value promises for industry, academia and society. Estimates suggest that in 2030, AI could contribute between $13 trillion[3] and $15.7 trillion[4] to global GDP. The common assumption underlying such estimates is that firms are and will widely adopt AI technologies[5] to transform products and services, processes and even entire business models to create value. The reality, however, portrays a different picture: organizations struggle to progress AI pilots and prototypes successfully into productive use and scalable market offerings. One of the main reasons for the lack of progress is the difficulty of making modern-day AI technologies (e.g., machine learning and deep learning[6]) broadly accessible to organizational members in a way that enables them to explore and realize valuable AI applications.

1 Hind Benbya is the accepting senior editor for this article.
2 We would like to thank Siemens for their excellent collaboration during our research. We would also like to thank the two anonymous reviewers and, especially, Senior Editor Hind Benbya for her specific advice that helped to improve this article. We would like to thank Walter Brenner for his feedback on an earlier version of this manuscript.
3 *Notes from the AI Frontier: Modeling the Impact of AI on the World Economy*, McKinsey&Company, 2018, available at https://www.mckinsey.com/~/media/McKinsey/Featured%20Insights/Artificial%20Intelligence/Notes%20from%20the%20frontier%20Modeling%20the%20impact%20of%20AI%20on%20the%20world%20economy/MGI-Notes-from-the-AI-frontier-Modeling-the-impact-of-AI-on-the-world-economy-September-2018.ashx.
4 *Sizing the Prize: What's the Real Value of AI for Your Business and How Can You Capitalise?* PWC, 2017, available at https://www.pwc.com/gx/en/issues/analytics/assets/pwc-ai-analysis-sizing-the-prize-report.pdf.
5 The term AI has been used since the 1950s to describe a variety of different technologies. Early research focused largely on decision support and expert systems, which use hard-coded decision rules based on expert knowledge and models that produce deterministic, nonadaptive systems. In this article, the term AI refers to the latest technologies that possess more advanced cognitive abilities beyond the simple automation of tasks (e.g., robotic process automation). For a brief history of AI and an overview of AI technologies, see Benbya, H., Davenport, T. H. and Pachidi, S. "Special Issue Editorial—Artificial Intelligence in Organizations: Current State and Future Opportunities," *MIS Quarterly Executive* (19:4), December 2020, pp. ix–xxi.
6 LeCun, Y., Bengio, Y. and Hinton, G. "Deep Learning," *Nature* (521:7553), May 2015, pp. 436-444.

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In this article, we use the term *democratizing AI* to describe the development of the organizational capability to identify, realize and scale AI use cases by involving and integrating the unique skills of domain experts, data scientists and IT professionals when introducing AI. The process of democratizing AI reflects an important paradigm shift: AI applications are not programmed, as in traditional software development, but trained based on algorithms and vast amounts of data. This shift from deterministic to probabilistic programming offers new application scenarios (i.e., making predictions and potentially decisions),[7] but it also poses new challenges for organizations.

Prior research has underlined the need to skillfully integrate domain and AI expertise when introducing AI systems because of the interdependencies of data, algorithms and domain knowledge.[8] A more recent study offers strategies to fully exploit AI's potential and mitigate unintended consequences by ensuring that employees understand the processes underlying AI-enabled decision-making and for guiding changes to their professional roles.[9] Though research on managing AI is still nascent, leading scholars have suggested that studying "democratizing data science and AI" will help to advance the productivity of data scientists and domain experts in organizations.[10]

To understand how organizations can democratize AI (i.e., develop the capability to broadly engage their employees when introducing AI systems), we conducted an in-depth case study of Siemens. Our research was guided by the research question: *How can organizations enable the democratization of AI?*

Our findings are based on the analysis of Siemens' AI journey.[11] We describe the evolutionary stages that Siemens progressed through as it democratized AI and analyze the specific activities that helped Siemens[12] drive business transformation using AI. We then provide a management perspective of how democratizing AI can strengthen the value and cost drivers of a business and conclude with recommended actions for executives and CIOs who want to engage their organization in harnessing the value potential of AI at scale. These recommendations are derived from the lessons learned at Siemens.

Defining AI Democratization

Merriam-Webster's dictionary highlights the accessibility and inclusiveness of the adjective "democratic," defining it as "relating to, appealing to, or available to the broad masses of the people." Consistent with this definition, we use the term *democratizing AI* as developing the organizational capability to make AI technologies relevant, appealing and available to a broad range of people within an organization when introducing AI. The term has been used by researchers as "... the notion that anyone, even those with little to no expertise, can perform data science if provided ample data and user-friendly analytics tools,"[13] and by practitioners who suggest "taking AI from the ivory towers and mak[ing] it accessible for all."[14] While the former perspective focuses on the provision of data and software tools to non-AI experts, the latter emphasizes the participation of all organizational members.

In our research, we focused on how organizations democratize AI by involving and integrating the unique skills of domain experts, data scientists and IT professionals when introducing AI.[15] This tripartite perspective accounts for the different backgrounds and skillsets of organizational members: domain experts contribute business and domain

7 von Krogh, G. "Artificial Intelligence in Organizations: New Opportunities for Phenomenon-Based Theorizing," *Academy of Management Discoveries* (4:4), December 2018. pp. 404-409.

8 van den Broek, E., Sergeeva, A. and Huysman, M "When the Machine Meets the Expert: An Ethnography of Developing AI for Hiring," *MIS Quarterly* (45:3), September 2021, pp. 1557-1580.

9 Mayer, A.-S., Strich, F. and Fiedler, M. "Unintended Consequences of Introducing AI Systems for Decision Making," *MIS Quarterly Executive* (19:4), December 2020, pp. 239-257.

10 Berente, N., Gu, B., Recker, J. and Santhanam, R. "Managing Artificial Intelligence," *MIS Quarterly* (45:3), September 2021, pp. 1433-1450.

11 See the Appendix for a detailed explanation of our research methodology.

12 When referring to Siemens, we include Siemens AG (www.siemens.com), with its Digital Industries, Infrastructure and Mobility businesses, Siemens Healthineers (www.siemens-healthineers.com), a publicly listed subsidiary, and Siemens Energy (www.siemens-energy.com), a publicly listed associate.

13 Benbya, H., Davenport, T. H., and Pachidi, S., op. cit., December 2020.

14 *Democratizing AI*, Microsoft News Center, September 26, 2016, available at https://news.microsoft.com/features/democratizing-ai.

15 Note that democratizing AI differs from democratizing IT, which primarily refers to the provision of software and tools to empower IT users to perform certain tasks (e.g., office tools, self-service portals, analytics dashboards or data).

Table 1: AI Adoption Challenges and their Practical Relevance

Description	Practical Relevance
Challenge 1: Defining AI Tasks	
AI applications perform narrowly specified tasks, and as such, the scope of an AI model is narrowly defined and reduced to a learning and optimization problem in data science (e.g., classifying images, sorting emails).	• Identifying valuable AI tasks is primarily in the competence of domain experts. • Integrating and evaluating performance outcomes of AI in processes, products, services or business models.
Challenge 2: Dealing with the Dual Role of Data	
Learning of AI systems often depends on the algorithmic processing of training data. AI systems can adapt to new data and changing environmental conditions through learning from new data. Data is the foundation for AI systems to acquire knowledge during learning. Data also serves as system input during operations.	• Identifying and assessing available datasets for learning AI. • Building hypotheses on causal relationships and selecting data features for learning AI models. • Monitoring, storing and federating data and the provisioning of computing infrastructure.
Challenge 3: Accepting that AI Outcomes Are Probabilistic	
AI applications follow a probabilistic operational logic. Outputs of AI systems are computed probabilities of the most likely outcome for a given input. Changes in input data to AI systems, or their application to slightly different problems, may produce significantly different, unforeseen or even undesired outcomes.	• Competence and tolerance of managers and users in handling systems that generate probabilistic outcomes. • Leveraging the adaptivity of AI systems to improve system performance over time. • Meeting regulatory and compliance requirements, which historically focused on deterministic systems.
Challenge 4: Addressing AI Black-Box Fears	
AI applications are likely to exhibit opaque behavior. AI technologies can exhibit a high degree of opacity due to the complex structure of their internal model, the dependency on data and the (continuous) learning process.	• Addressing doubts, fears and potentially new ethical or moral challenges that are evoked by AI. • Finding ways to develop and maintain users' trust in AI systems.

understanding, data scientists process and develop methods to build AI models, and IT professionals make the software tools and platforms available to enable the scaling of AI into productive information systems.

Democratizing AI Helps Organizations to Address AI Adoption Challenges

Over the past decade, AI has become increasingly relevant for organizations because it allows entirely new applications[16] such as image classification, voice recognition and detecting patterns in large data sets. Firms seek to deploy AI productively to generate business value but often fail to do so due to the challenges related to the latest AI technologies. We outline how these AI characteristics impose challenges to the organizational adoption of AI and indicate their practical relevance (see Table 1).

Challenge 1: Defining AI Tasks

AI applications solve specific tasks with data for a narrowly defined business problem. Valuable business problems tend to originate from competent business users or domain experts rather than data scientists, who predominantly focus on mathematical

16 von Krogh, G., op. cit., December 2018.

optimization and model performance. Moving from idea to implementation and scaling of AI requires the collaboration of interdisciplinary teams that can solve significant, well-defined problems with AI and competently evaluate the business outcome of the solution.[17]

Challenge 2: Dealing with the Dual Role of Data

The learning of an AI system largely depends on training, with the system identifying structures, patterns and knowledge stored in the data to generate AI models.[18] This iterative, computationally intensive process generates AI models that are influenced by the selected learning algorithm, its parameterization and the processed training data.[19] AI models can then be used to make predictions based on new input data. This dual role of data (i.e., as input for learning and as input for making predictions) requires not only data that are available and potentially curated but also competencies to build hypotheses for selecting relevant data features. From an IT perspective, learning poses requirements for model storage and data federation[20] as well as for processing during AI system development and operation.

Challenge 3: Understanding that AI Outcomes Are Probabilistic

AI applications follow a probabilistic operational logic and constantly require confident, empowered users who can tolerate the probabilistic outcomes of such systems. For example, changes in input data to AI systems, or their application to slightly different problems, may produce significantly different, unforeseen or even undesired outcomes. As such, AI systems must be constantly monitored and may require retraining with new data over their lifecycle.[21] On the positive side, it is precisely this adaptivity of AI systems that enables new, previously impossible application scenarios.

Challenge 4: Addressing AI Black-Box Fears

Although AI applications can have a black-box character, they can also reshape how humans cooperate with machines. When AI is used to augment or sometimes replace humans, the enabled decision-making processes are often considered to be a black-box approach.[22] Firms that seek to deploy AI need to proactively address the doubts, fears and potentially new ethical or moral challenges that are evoked by the inherent technology characteristics of AI.

Democratizing AI Fosters Collaboration to Address the Challenges

Democratizing AI helps organizations address each of these four challenges, which are particularly prevalent in the business and data science domains but need to be carefully addressed by the CIO and IT function when adopting and scaling AI broadly (see Figure 1). More specifically, democratization enables domain experts, data scientists and IT professionals to work together to identify and design valuable tasks to be solved by AI, what data are to be used for training and operating AI, and how probabilistic outcomes of AI systems are integrated successfully into the business domain in the light of AI systems' opaque behavior.

17 Interdisciplinary teamwork was also important for earlier generations of analytical systems (e.g., decision support systems, data warehousing and big data analytics). This is even more true for developing advanced cognitive systems, such as AI systems, which require the integration of business knowledge, analysis and modeling skills, and data management expertise, which is typically only available in specialized roles. For further information, see Watson, H. J. "Preparing for the Cognitive Generation of Decision Support," *MIS Quarterly Executive* (16:3), September 2017, pp. 153-169.

18 The concepts of how machines learn are explained particularly well in the chapter "Learning from Examples" in the seminal book by Stuart Russell and Peter Norvig. See Russell, S. J. and Norvig, P. *Artificial Intelligence: A Modern Approach*, (3rd ed.), Pearson Education, 2016.

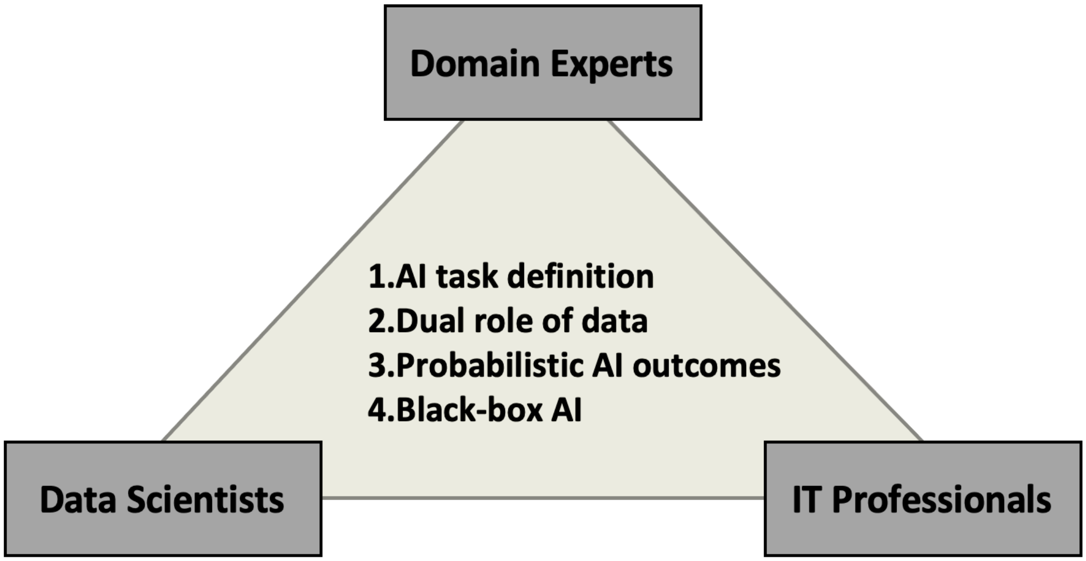
19 For an introduction to machine learning and deep learning, and different types of learning, see Janiesch, C., Zschech, P. and Heinrich, K. "Machine Learning and Deep Learning," *Electronic Markets* (31:3), Springer, 2021, pp. 685-695.

20 Data federation, sometimes referred to as data virtualization, is an approach to collecting, storing and making use of data through virtualization rather than by physical storage of a dedicated database.

21 A recent study of an AI-enabled online tracking system (MarineTraffic.com) finds that enrolling domain expertise is essential for generating a ground truth and assessment of algorithmic output and for altering algorithm and data acquisition architectures, and underlines the need for business user involvement during system development and use. See Grønsund, T. and Aanestad, M. "Augmenting the Algorithm: Emerging Human-in-the-Loop Work Configurations," *The Journal of Strategic Information Systems* (29:2), June 2020.

22 Explaining the black-box behavior of AI systems is challenging and sometimes even impossible. However, organizations can adopt different measures to "deploy AI applications in a legal, ethical and safe manner" in order to establish trust and confidence in AI-based decisions. For more information, see Asatiani, A., Malo, P., Nagbøl, P. R. and Penttinen, E. "Challenges of Explaining the Behavior of Black-Box AI Systems," *MIS Quarterly Executive* (19:4), December 2020, pp. 259-278.

Figure 1: Conceptual Model of How Democratizing AI Addresses the Adoption Challenges



Below, we describe the activities Siemens took as it democratized its AI capability. The Siemens case is instructive for two reasons. First, Siemens is a leading organization with considerable experience deploying and scaling AI across a variety of applications, and it has established and exploited its democratization capability to successfully overcome hurdles in organizational AI adoption. Second, we were able to study and compare multiple AI use case contexts within Siemens by carrying out in-depth investigations of how the democratization of AI was implemented in both Siemens' healthcare and manufacturing divisions.

Siemens Corporate Background

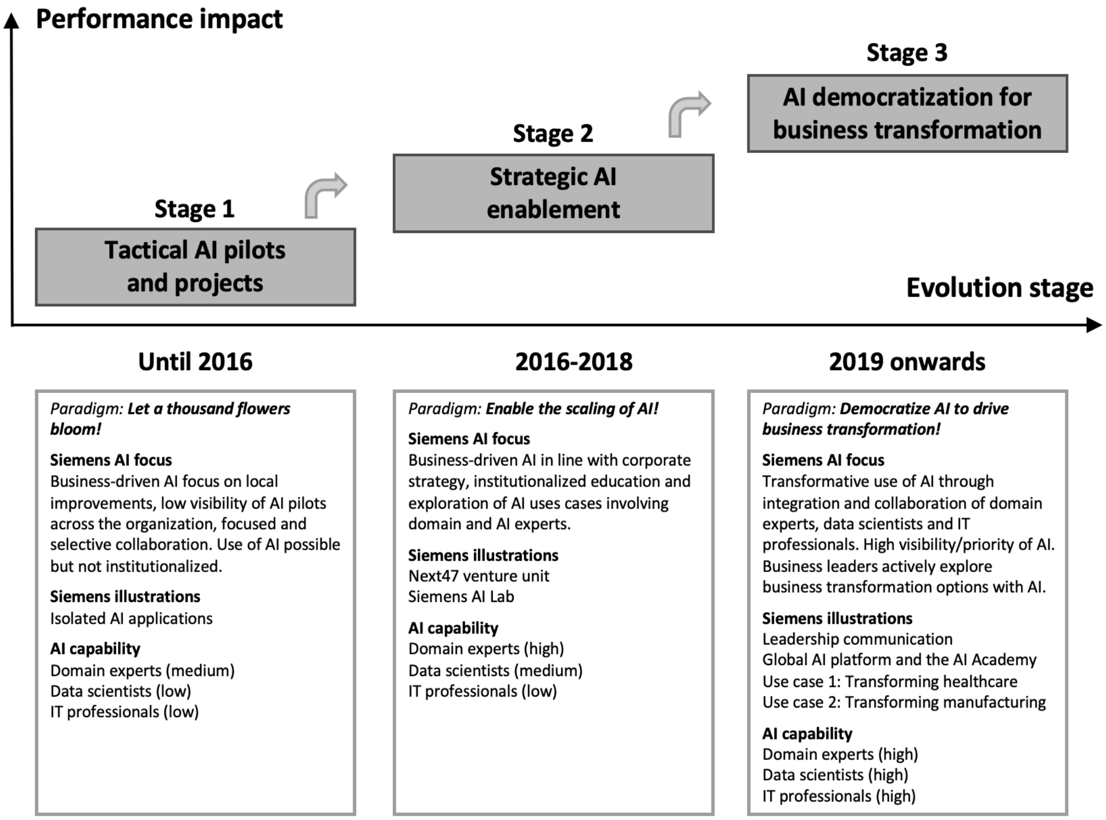
Siemens was founded in 1847 and has been continually committed to creating value for its customers, driven by its innovation capacity. By 1990, Siemens was organized as a group of largely independent business units that served their specific markets. During the 1990s and early 2000s, the business portfolio was streamlined and, in 2008, a new corporate structure with industry, energy and healthcare sectors was introduced, with these sectors later transitioning into operating and strategic companies. Each of these companies focused on its specific market with a high level of independence. Siemens' management drove this specialization further by spinning off its healthcare and energy businesses in 2018 and 2020, respectively. Today, three separately managed companies—Siemens, Siemens Healthineers and Siemens Energy—form a powerful ecosystem to tap the value-creating potential of individual businesses.

Siemens' use of AI evolved with the organizational structure. Following the deployment of isolated AI use cases across organizational subunits, Siemens' democratization of AI aimed at scaling AI efficiently to provide customer value while supporting the increased specialization of its businesses. Since then, Siemens has used AI to transform various processes, products and services in its energy, healthcare and industrial businesses.

Siemens' Evolutionary Stages to Democratizing AI

Siemens' democratization of AI evolved through three stages. Each stage has a different focus and enhanced the collaboration between

Figure 2: Siemens' Three Stages to Democratizing AI



domain experts, data scientists and IT professionals (see Figure 2).

Stage 1: Tactical AI Pilots and Projects

In Stage 1, Siemens implemented tactical AI pilots and projects. AI was focused on local improvements, which were driven by individual domain experts and small teams in the business. Examples include the recognition of handwritten zip codes in Siemens' postal sorting system,[23] a fully automated driverless subway system and basic voice-enabled self-services for call centers. These AI solutions were independently developed with minimum integration into Siemens' IT-application landscape. Wider awareness through Siemens was limited, and specialists were hired for solving focused AI problems.

During the tactical stage, which lasted until 2016, AI was used but not institutionalized across the organization, and the role of data scientists and IT professionals was ad hoc. The paradigm for this stage was *Let a thousand flowers bloom*!

Stage 2: Strategic AI Enablement

In Stage 2 (2016-2018), Siemens' focus shifted toward strategic AI enablement. Senior leadership communicated the importance of AI for supporting the business strategy, which focused on digitalization. During this stage, AI applications, either as stand-alone offerings or as embedded software solutions, were seen as drivers for differentiation, as stated by Joe Kaeser, former CEO of Siemens: "Artificial intelligence is here and being rapidly commercialized, with new applications being created not just for

23 For a description of how Siemens used a neural network to interpret handwritten zip codes, see Pfister, M., Behnke, S. and Rojas, R. "Recognition of Handwritten ZIP Codes in a Real-World Non-Standard-Letter Sorting System," *Applied Intelligence* (12:1), January 2000, pp. 95-115.

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manufacturing but also for energy, healthcare, and oil and gas. This will change how we all do business."[24]

In 2016, Siemens established Next47, a venture unit. One of this unit's innovation areas is sourcing AI applications from startups that can be scaled into business solutions. In 2017, Siemens also launched its AI Lab close to its Munich headquarters. The lab's team has run hundreds of workshops where domain experts worked with data scientists in an experimental setting to create ideas for AI use cases. Domain experts and data scientists from the business units were assigned to the AI Lab for a week, and the streamlined process for onboarding them into the AI community followed proven collaborative workshop formats targeted at their different backgrounds and levels of AI experience. The team rapidly demonstrated the value of the lab: "This kind of focused co-creation between Siemens' business units and its development department very quickly produces results that make the vague term 'AI' concrete" (Dr. Ulli Waltinger, Head of Siemens AI Lab).

The AI Lab has facilitated the creation of huge numbers of AI use cases for Siemens' business units, ranging across manufacturing, medical technology and even the management of administrative tasks, thereby laying the grounds for Siemens' further AI journey.

Stage 2 created the breeding ground for efficiently exploring and shaping valuable AI potential by facilitating the collaboration of domain and data science experts. The paradigm for this stage was *Enable the scaling of AI!*

Stage 3: Democratizing AI for Business Transformation

Stage 3 began in 2019 and is ongoing. In 2019, Siemens' AI focus moved toward realizing and scaling AI applications that have the potential to transform products, services and processes, as highlighted by Dr. Roland Busch, former CTO, and now CEO of Siemens:[25] "We currently stand at a crucial point in AI's evolution: we're on the verge of breaking into exponential growth. And there's still plenty of untapped potential."[26]

To realize this untapped potential, the effective collaboration of domain experts, data scientists and IT professionals became an essential capability for Siemens: "There's a form of AI that we can all benefit from: AI that's integrated into industrial processes to create value on an industrial scale which combines AI with domain know-how"[27] (Dr. Roland Busch). During Stage 3, Siemens' IT leadership has been investing in processes and infrastructures to further scale AI and make AI knowledge widely accessible within the organization. First, a global AI platform for data collection, aggregation and support of machine learning workflows was incorporated into the IT strategy. Implementation of this platform commenced soon after to accelerate the adoption of AI tools and frameworks and secure efficient scaling and integration of AI applications. Second, the IT organization launched the AI Academy, which offers individual learning paths for employees with different levels of AI literacy. The AI Academy addresses upskilling within the IT organization and the need to build further AI knowledge.

As of today, Siemens has successfully launched many transformative AI applications in its energy, healthcare and industrial businesses, driven by the successful collaboration of domain experts, data scientists and IT professionals. The paradigm for Stage 3 is *Democratize AI to drive business transformation!*

Siemens' AI Use Cases

We selected use cases in two of Siemens' businesses (healthcare and manufacturing) to illustrate how democratizing AI has enabled the transformation of a healthcare product and a manufacturing process. Tables 2 and 3 indicate the case-specific AI challenges and the AI democratization activities carried out, and relate these activities to the four AI adoption challenges described above. The use cases highlight not only the importance of involving domain experts, data scientists and IT professionals when introducing

24 Kaeser, J. *Why Robots Will Improve Manufacturing Jobs*, Time.com, September 14, 2017, available at https://time.com/4940374/joe-kaeser-siemens-robots-jobs/.

25 Dr. Roland Busch became president and chief executive officer of Siemens AG in January 2021.

26 Busch, R. *"Industry is Where the Real Potential of AI Lies,"* World Economic Forum, January 21, 2019, available at https://www.weforum.org/agenda/2019/01/industry-is-where-the-real-potential-of-ai-lies/.

27 Busch, R., op. cit., January 21, 2019.

Figure 3: Medical Image Analysis Using AI Companion[28]

AI but also their contributions to AI-enabled transformations.[28]

1. Healthcare Use Case: How Democratizing AI Supported the Transformation of a Healthcare Product

Siemens Healthineers developed "AI Companion," an AI-based software suite used to transform radiological diagnostics and patient treatment planning. The product comprises multiple AI applications (e.g., "AI Rad Companion and "AI Pathway Companion"), which leverage medical data sources for improving diagnostic workflows and enabling personalized patient treatment planning (see Figure 3). Table 2 summarizes the AI democratization activities that were used to effectively address the AI challenges of developing and operating AI Companion.

Defining the Right AI Tasks. The challenge for the AI Companion product teams was to understand the particular activities and information needs in the workflows of domain experts (e.g., radiologists, oncologists and cardiologists) and identify tasks that could be performed well with AI. This challenge was addressed by building cross-functional product teams with permanent data science representation. Siemens product teams traditionally included product managers, R&D experts, and software architects and developers. For AI Companion, however, it was crucial to integrate data scientists into the product teams and facilitate an ongoing dialogue about how AI could be leveraged to find a solution for clinical needs.

Ensuring User Trust in AI Companion. Introducing probabilistic AI applications that potentially exhibit black-box behavior was a particular challenge:

> *"They [urologists] don't care about the [AI] method, but what they want is transparency on how you come to those results. We cannot say, "we used your data, and we applied deep learning, and the system shows that this is a good option for this patient." [If we do] they will never have trust in this system."* Program Lead, AI Companion Product Team

28 *AI-Rad Companion*, Siemens Healthineers, 2020, available at https://www.siemens-healthineers.com/digital-health-solutions/digital-solutions-overview/clinical-decision-support/ai-rad-companion.

Table 2: Democratization of AI in the Healthcare Use Case*

Case-Specific AI Challenges	AI Democratization Activities	Task	Data	Prob	Black Box
Defining the right AI tasks	Building cross-functional product teams with permanent data science representation	X			
Ensuring user trust in AI Companion	Co-developing AI models and applications with users and customers			X	X
Managing training data acquisition	Partnering with research institutions and establishing a scalable data infrastructure for AI		X		
Addressing quality assurance and regulatory requirements	Managing learning and adaptivity of the AI system along the entire AI product lifecycle			X	X

* AI adoption challenges: (T) AI task definition; (D) Dual role of data (P); Probabilistic AI outcome; (B) Black-box AI

This challenge was addressed by co-developing AI models and applications with users. Because it was important to design AI Companion so that it was as transparent and explainable as possible, the product teams consistently involved clinicians in the AI model-building and application-design process. To be accepted by clinicians, AI Companion must provide detailed information about the AI-generated outcomes, including its influencing parameters:

> *"We co-create with clinicians. We show them iterations—and it is not only one iteration—but we continuously build and have feedback until they feel very good about the system. And we think about how we can easily show the parameters in the user interface, explain the result and how we came to that in a simplified way. You can drill down into the details if you want until you build trust in the system. We cannot say, "It is a black box, with five parameters in and out comes one score." That doesn't work."* Program Lead AI Companion Product Team

Managing Training Data Acquisition. Acquiring training data was challenging because different AI models require various types of data, such as medical images, patient lab reports, treatment data and therapy outcomes, all of which are generated in hospitals and research institutions and are not directly accessible. Furthermore, improving AI models over time requires the regular federation of data for retraining, which was another data collection challenge. This challenge was addressed through partnering with research institutions and establishing a scalable data infrastructure for AI. Siemens Healthineers has established partnerships with healthcare providers, research institutions and hospitals to access and manage training data acquisition and curation. These collaborations are enabled through a scalable data infrastructure that was launched in 2020 and allows federated data and AI models to be securely shared.[29]

Addressing Quality Assurance and Regulatory Requirements. The development and operation of medical software applications are documentation intensive and typically follow a waterfall development approach. The characteristics of AI Companion, particularly its training data dependency, the generation of probabilistic outcomes and the potential black-box character of AI, challenged traditional quality assurance and regulatory processes and roles. This challenge was addressed by managing learning and the adaptivity of the AI system along the entire AI product lifecycle. More specifically, the product teams enhanced the software quality management approach to demonstrate continuous improvement for AI model upgrades and to ensure that AI models in operation were not degrading.

29 *Teamplay Digital Health Platform*, Siemens Healthineers, 2021, available at https://www.siemens-healthineers.com/en-us/digital-health-solutions/teamplay-digital-health-platform.

Figure 4: Siemens' Industry 4.0 Factory in Amberg

2. Manufacturing Use Cases: How AI Democratization Supported Transformation of a Manufacturing Process

Siemens Digital Industries produces automation equipment at its smart factory in Amberg, Germany (see Figure 4). The highly automated plant manufactures 1,200 different products for over 60,000 customers. Among other components, these products include printed circuit boards (PCBs). We describe two AI applications that have transformed manufacturing in Amberg.[30] The first is "AI for in-line quality prediction," which eliminates a production bottleneck in the quality control of PCBs by predicting whether or not additional x-ray quality testing is necessary. The second is "AI for predictive maintenance," which reduces the unplanned downtime of a PCB milling machine to smooth production flow. Table 3 summarizes the AI democratization activities that were used to effectively address the challenges of transforming manufacturing with AI at Siemens.

30 The Siemens Amberg plant has implemented many more AI applications. The two described are particularly suited to illustrate how AI has transformed manufacturing. They have also been reported in technical research and media publications.

Introducing a Probabilistic System into a Successful Manufacturing Organization. The Amberg plant operates at a 99.9996% quality level, has increased its productivity by a factor of 14 since 1990 and handles 350 manufacturing changeovers daily. When quality testing of PCBs created a bottleneck, plant management had two options: invest €500,000 ($508,400)[31] in another x-ray tester, a secure and well-known solution, or try to predict the likelihood of manufacturing defects in PCBs using production data and AI algorithms. Exploring the AI option also required some investments but it was unknown whether the outcome could ever meet the plant's high-quality requirements. Leaders at the Amberg plant addressed this challenge by revising investment decisions in light of AI possibilities. Despite the exploratory and experimental nature of the AI-based solution, the management team was willing to commit to using process data for decision-making and was keen to adopt new organizational practices (i.e., trusting a probabilistic AI system to eliminate the testing for about half of the PCBs) to realize the value potential of AI.

31 Currency conversion as of August 2022.

Table 3: AI Democratization in the Manufacturing Use Cases*

Case-Specific AI Challenges	AI Democratization Activities	Task	Data	Prob	Black Box
Introducing a probabilistic system into a successful manufacturing organization	Revising investment decisions in light of AI possibilities			X	X
Identifying valuable AI use cases for a manufacturing context	Generating AI use case ideas collaboratively involving process engineers and manufacturing specialists Providing data and AI self-service tools to data scientists	X	X		
Extracting and assessing manufacturing process data for AI model building	Conducting data exploration and data understanding workshops		X	X	X
Enabling scaling of successful AI applications across Siemens' manufacturing network	Disseminating best practices and AI showcases within the manufacturing network Connecting to a cloud-based IT infrastructure that allows AI scaling across manufacturing plants	X	X		

* AI adoption challenges: (T) AI task definition; (D) Dual role of data; (P) Probabilistic AI outcomes; (B) Black-box AI

Identifying Valuable AI Use Cases for a Manufacturing Context. Initially, the management team at the Amberg plant attempted a "big-bang" approach by providing data scientists with production data to generate AI use cases. However, the team quickly realized that this approach did not work:

> *"In the early days, we tried a lot to leverage the big bang approach (i.e., connect all the data), collect everything, tip it over the fence to the data scientists, and then they will find the golden nugget). This has turned out to be the wrong way, and without domain know-how, we see it as virtually impossible to use AI to increase productivity."* Head of Strategic Digitalization, Siemens Amberg

Data scientists alone could not uncover the "right" use cases or fully interpret the data. This challenge was addressed by generating AI use case ideas collaboratively by involving process engineers and manufacturing specialists. This domain expertise was a crucial ingredient for identifying where AI could be used in the plant:

> *"It took us a very long time to identify, tackle and implement good predictive maintenance cases. But once the first seeds had been planted, it became much easier to find new use cases. We then presented the topics to our maintenance personnel, and new use cases actually emerged from the team because they were very well able to interpret whether this is transferable to other use cases."* Head Strategic Digitalization, Siemens Amberg

The challenge of identifying AI use cases was also addressed by providing data and AI self-service tools. To further leverage the process knowledge of Amberg's manufacturing personnel, data scientists and IT professionals provided AI self-service tools so that domain experts could prepare AI use cases on their own and then have data scientists support the AI modeling. By using the tools, these experts enhanced their understanding of data sources, as well as the required structure, volume and quality of data needed for training AI systems, effectively bringing domain and data scientists closer together.

Extracting and Assessing Manufacturing Process Data for AI Model Building. Understanding the large volumes of available production data was a key challenge for using AI at the Amberg plant. Technically, there was no difficulty in collecting data from manufacturing equipment, but data scientists lacked the understanding of the shop floor environment to make sense of machine and process parameters and to develop hypotheses on influencing factors. This challenge was addressed by conducting data exploration and data understanding workshops in which manufacturing specialists and data scientists collaboratively investigated and assessed the content and quality of available data and process-relevant features required for training AI models. For example, over 40 different data sets with a vast range of features were assembled and jointly examined for predictive maintenance of the PCB milling machine. Eventually, however, the maintenance prediction could be reduced to just two variables.

Enabling Scaling of Successful AI Applications Across Siemens' Manufacturing Network. Siemens' Amberg plant is part of a global manufacturing network of approximately 30 factories. Naturally, Siemens' ambition was to scale AI across this network, but it faced two scaling challenges. The first was defining opportunities for scaling successful AI applications (e.g., in-line quality control) for similar tasks in other plants. This challenge was addressed by regularly exchanging best practices and AI showcases within the manufacturing network. The second challenge was ensuring it had the ability to transfer data and, in particular, the deployed AI models. This challenge was addressed by connecting to a cloud-based IT infrastructure that allows AI scaling across manufacturing plants. On the one hand, this infrastructure enables machine control via the local manufacturing execution system, which controls the x-ray tester and interfaces to the milling machine. On the other hand, the cloud environment serves as a basis for the future data federation and distribution of developed and deployed AI models.

Value and Cost Impacts of AI Democratization at Siemens

Table 4 summarizes the AI democratization activities that Siemens carried out to address each of the four AI adoption challenges and their impacts on value and cost. Overall, democratizing AI facilitated value exploration and realization while assuring efficient provisioning and scalability of AI.

Democratizing AI Generates Value and Cost Benefits

So far in this article, we have described how Siemens built the organizational capability to identify, realize and scale AI use cases by leveraging the skills of domain experts, data scientists and IT professionals—i.e., how it democratized AI. For Siemens, however, as for many companies, AI democratization is not an end in itself but a means toward realizing the broad and profitable use of AI, as Dr. Roland Busch pointed out in an address to the World Economic Forum in 2019: "In order for the balance sheet of AI applications to be positive, companies—including large corporations, small and medium-sized businesses, and even tradespeople—must be able to deploy AI in a broad and profitable manner."[32]

AI democratization enhances an organization's ability to generate value from AI, as indicated in the value-cost framework[33] shown in Figure 5. Key drivers include the customer value of an AI application, which is based on the valuation of an internal or external customer, and the firm's cost of providing the AI application. The framework focuses the discussion on how AI democratization raises customer value and lowers the costs of providing AI applications.

How AI Democratization Generates Value

Democratization is a value driver for AI because the exploration and realization of valuable AI potential are rooted in deep domain

32 Busch, R., op. cit., January 21, 2019.

33 The value-cost framework assumes that a superior market position is primarily driven by generating high customer benefits produced at a low cost to the firm. For an excellent introduction to the value-cost framework, see Walker, G., and Madsen, T. L. *Modern Competitive Strategy*, (Vol. 4), McGraw Hill, 2015.

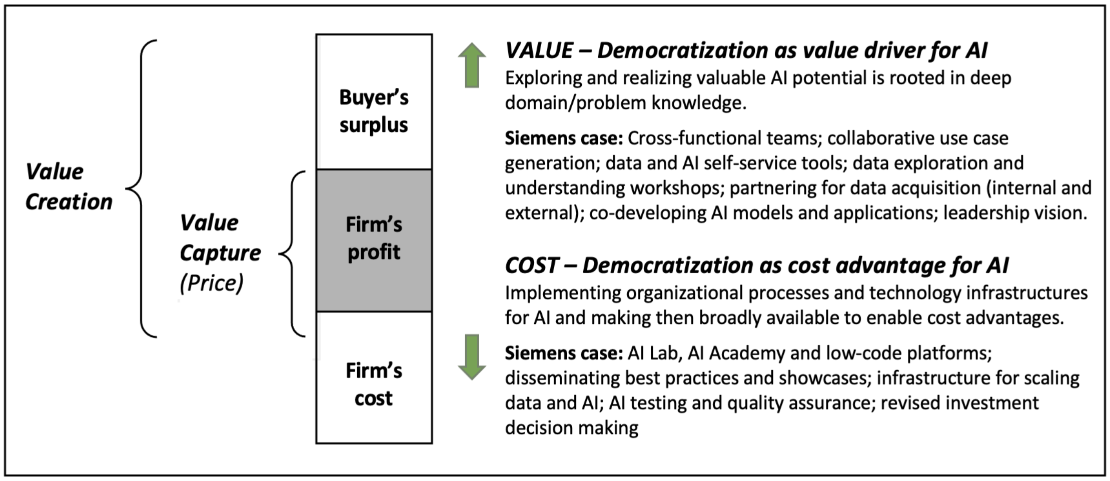
Table 4: Impacts of Siemens' AI Democratization Activities on Value and Cost

AI Adoption Challenge	Value Impact of AI Democratization at Siemens	Cost Impact of AI Democratization at Siemens
1) Defining AI Tasks	**Democratization drives effective AI task design.** In both the healthcare and manufacturing use cases, domain, data science and IT experts engaged deeply in identifying and generating use case ideas and defining AI tasks that were valuable in their respective domains. The key challenge in the radiology context was to design and integrate AI-enabled tasks into clinicians' workflows, whereas the manufacturing setting required a more systematic exploration of AI use cases, which was supported by showcases, collaborative workshops and IT-provided data and self-service tools. **Case evidence** • Cross-functional product teams with data scientists (healthcare). • Generating AI use case ideas collaboratively involving process engineers and manufacturing specialists (manufacturing). • Identifying valuable AI use cases by providing data and AI self-service tools to data scientists (manufacturing).	**Democratization facilitates efficient onboarding of domain experts to the AI community, and the scaling of AI tasks through knowledge transfer.** The AI Lab, AI Academy and low-code platforms provided a foundation for onboarding domain experts and the exploration of scaled AI tasks. Democratizing AI also facilitated knowledge transfer—e.g., through best-practice exchanges and AI showcases within Siemens' manufacturing network—to stimulate the efficient scaling of AI systems into similar use contexts. **Case evidence** • Siemens' AI Lab allows the efficient onboarding of domain experts as a collaborative experience (corporate initiative). • Siemens' AI Academy provides scalable education formats to enhance efficient dissemination and learning about AI by interested individuals (corporate initiative). • Disseminating best-practice and showcases within the manufacturing network to stimulate scaling of AI (manufacturing).
2) Dealing with the Dual Role of Data	**Democratization helps to derive value from data.** Siemens generated business value by leveraging AI systems that could learn and adapt to new data. The democratization activities in the use cases focused on exploring training data, understanding data and identifying features (e.g., for building hypotheses and AI models), as well as the ongoing acquisition of training data to ensure and improve system performance, even during deployment. In all the use cases, the collaboration between domain experts and data scientists was crucial, and, in the healthcare case, even integrated externally generated data from hospitals. **Case evidence** • Partnering with research institutions for accessing externally generated training data (healthcare). • Extracting and assessing manufacturing process data for AI model building through data exploration and data understanding workshops (manufacturing).	**Democratization assures efficient operation and scaling of AI through data and AI infrastructures.** One important aspect of dealing with the dual role of data efficiently was the monitoring, storing, and federating of training data through scalable data and cloud-based IT infrastructures. Democratizing AI enabled connectivity between Siemens' manufacturing plants and hospitals not only for accessing and federating training data, but also for enabling the cost-efficient scaling of AI solutions across a wider range of manufacturing plants and hospitals. **Case evidence** • Establishing scalable data infrastructure for managing AI training data acquisition and federation (healthcare). • Connecting to a cloud-based IT infrastructure to enable efficient scaling of AI across manufacturing plants (manufacturing).

Table 4: Impacts of Siemens' AI Democratization Activities on Value and Cost

AI Adoption Challenge	Value Impact of AI Democratization at Siemens	Cost Impact of AI Democratization at Siemens
3) Accepting that AI Outcomes Are Probabilistic	**Democratization drives acceptance of probabilistic AI outcomes.** Siemens involved domain experts early on to identify and mitigate critical issues relating to probabilistic AI outcomes. In the use cases, AI-enabled value generation was tolerated by end users, because domain experts addressed concerns and questions, and provided guidance about how end users will handle probabilistic AI outcomes in their application context. For example, in manufacturing, only parts with a very low likelihood of failure were not processed through an x-ray quality control. Furthermore, Siemens' senior management publicly discussed the company's value potential of AI, thereby bolstering managers' and users' confidence in AI. **Case evidence** • Co-developing AI models and applications with users and customers (healthcare). • Conducting data exploration and data understanding workshops (manufacturing). • Siemens leadership communicating an AI vision and serving as role model (corporate initiative).	**Democratization involves domain experts in the risk-controlling use of AI.** The involvement of domain experts was useful for efficiently managing the risks associated with probabilistic AI outcomes. In the healthcare use case, quality assurance, regulatory and product experts modified their quality management approach to account for data dependency and probabilistic outcomes, thereby ensuring efficient handling of the AI system's outcomes over time. In the manufacturing use cases, plant management revised investment decision-making to consciously balance exploration and experimentation with probabilistic AI systems through step-by-step developments and gradually rolling out successful AI solutions into other application areas and manufacturing sites. **Case evidence** • Managing learning and adaptivity of the AI system along the entire AI product lifecycle (healthcare). • Revising investment decisions in light of AI possibilities (manufacturing).
4) Addressing AI Black-Box Concerns	**Democratization proactively addresses AI opacity.** In the healthcare use case, data scientists and user researchers worked closely to understand clinicians' explainability needs and tolerances for opaque AI, resulting in adaptations of the user interface, workflow design or chosen AI model. For example, the AI system was designed to not independently make health-related decisions without involvement of clinicians. In the manufacturing use cases, domain experts focused on understanding how data and selected features would impact prediction quality and how the value of the AI application was demonstrated. In all the use cases, close collaboration and involvement was crucial for proactively addressing the doubts, fears and concerns evoked by AI opacity. **Case evidence** • Co-developing AI models and applications with users and customers (healthcare). • Conducting data exploration and data understanding workshops (manufacturing).	**Democratization supports proactive dialogue on the limitations of AI predictions**. Involving domain experts, data scientists and IT specialists in the development of AI systems was useful for efficiently dealing with the inscrutability and potential lack of explainability of AI. The involvement of healthcare quality assurance experts led to standardized quality management measures (e.g., testing), which enhanced confidence in the AI system's performance. By changing investment decision-making in favor of AI, the manufacturing leadership team cultivated and allowed manufacturing experts to explore and experiment with AI, which encouraged a dialogue where doubts and fears about AI could be raised and addressed proactively. **Case evidence** • Managing learning and adaptivity of the AI system along the entire AI product lifecycle (healthcare). • Revising investment decisions in light of AI possibilities (manufacturing). • Communicating openly about AI at all organizational levels (corporate initiative).

Figure 5: How Democratization Affects the Value and Cost of AI



and problem knowledge. The Siemens use cases include many activities where business and domain experts collaborated with data scientists to drive the value of AI while addressing AI adoption challenges. In the healthcare example, clinicians and data scientists collaborated with product teams to identify valuable AI tasks. These activities were explorative and iterative at the beginning and subsequently evolved into co-developing AI applications that established confidence with end users and ensured that the final product was valuable to the target user group. In the manufacturing examples, Siemens' plant leadership endorsed the experimental, data-intensive and hypothesis-driven development of AI applications. Collaborative use case idea-generation and data-exploration workshops as well as the provision of AI self-service tools were critical for empowering plant personnel and leveraging existing domain knowledge. The Siemens use cases clearly show that valuable AI applications can only emerge through the cooperation of domain experts and data scientists.

Another important benefit of AI democratization is that it facilitates the increase of value through scaling AI. The Siemens AI applications described above were initially developed as solutions for local, isolated problems, but their scaling to internal and external partners was envisioned right from the outset to increase their overall value.

How AI Democratization Generates Cost Advantages

Democratization produces cost advantages for AI by implementing standardized organizational processes and technological infrastructures for developing and deploying AI. Democratizing AI at Siemens generated at least two types of cost advantages. The first was that it allowed Siemens to move up the learning curve faster by standardizing the generation of training data and AI use cases. The AI Lab provided streamlined onboarding processes for domain experts and data scientists and proven collaborative workshop formats for generating use case ideas; later, the teams in healthcare and manufacturing used long-term approaches to collaboratively develop AI applications and stimulate the efficient scaling of AI applications through disseminating best practices and showcases. Such learning was critical for Siemens because AI applications require more experimental and data-driven approaches than traditional software applications, for which many development frameworks and methods already exist.

The second cost advantage came from economies of scale and scope as Siemens committed to the broad and diverse use of AI. On the one hand, fixed costs for standardized

Table 5: Recommendations for Driving AI Democratization

<table>
<tr><th colspan="2">Value Impact of AI Democratization at Siemens</th></tr>
<tr><th colspan="2">Lesson 1: Promote Communication about AI to Build Trust</th></tr>
<tr><td colspan="2">Recommendations
1.1. Communicate a vision and explain how AI creates value for the organization.
1.2. Promote communication about AI at all organizational levels to build trust.</td></tr>
<tr><td colspan="2">Driver: Senior executives (including CIOs).</td></tr>
<tr><th>AI Democratization as Value Driver</th><th>AI Democratization as Cost Advantage</th></tr>
<tr><th>Lesson 2: Enable the Sustainable Exploration and Realization of AI Value Potential</th><th>Lesson 3: Ensure Efficient Provisioning and Scalability of AI</th></tr>
<tr><td>Recommendations
2.1. Engage domain experts deeply in AI-based value generation to capture relevant business opportunities.
2.2. Create a breeding ground for exploring data value and generating AI use case ideas and realizing them.
2.3. Adopt a value-oriented perspective on AI aligned with the business strategy, corporate structure and culture.</td><td>Recommendations
3.1. Encourage learning about AI technology for different levels of AI literacy and facilitate AI knowledge transfer.
3.2. Establish data and AI infrastructures to enable efficient operation and scaling of AI.
3.3. Focus on cost-efficient provisioning of AI applications rather than technological perfection.</td></tr>
<tr><td colspan="2">Driver: Domain experts, data scientists and IT professionals.</td></tr>
</table>

organizational processes and technological infrastructures can be spread across a larger number of AI applications. On the other hand, a large and diverse set of operational AI applications creates opportunities for sharing and transferring AI assets (e.g., training data, AI models, AI applications) across different business contexts or geographical locations. Siemens Healthineers, for example, created a scalable data infrastructure primarily managed by the IT organization not only to leverage the adaptivity and learning capability of AI systems, but also to ensure their long-term scalability. In the manufacturing examples, the IT organization managed the cloud connectivity of the plant and the integration of AI applications into the software landscape (e.g., the manufacturing execution system) and ensured the technical scalability of AI applications in the manufacturing network.

Lessons Learned and Recommended AI Democratizing Actions

The Siemens use cases demonstrate that scaling AI holds significant value potential and that overcoming AI adoption challenges requires the successful collaboration of business and domain experts, data scientists and IT professionals. Furthermore, Siemens' AI democratization journey shows that AI value potential and use cases primarily emerge through the collaboration of business and data science experts. This is because AI systems solve narrowly specified tasks, learn from data (which often can only be interpreted by domain experts), generate probabilistic outcomes and can exhibit opaque behavior.

These findings are highly relevant for CIOs and the role of IT: CIOs can play a key role when their organizations adopt AI broadly by ensuring the efficient provisioning and scalability of AI, and especially by collaborating with data science teams. Based on our analysis of the Siemens use cases, we have identified three lessons learned and eight recommended actions derived from the lessons on how CIOs and senior business leaders can democratize AI (see Table 5).

Lesson 1: Promote Communication about AI to Build Trust

Dialogue is the foundation of democratization. AI is perceived not only as an opportunity but also as a technical, ethical or societal threat. Given the hype, skeptical reporting and often vague understanding of AI's functioning, in combination with its technological properties, it is crucial that senior executives address the significant potential for misinformation and facilitate an approach that embraces dialogue between business, data science and IT representatives. We provide the two following communication recommendations for executives who seek to democratize AI in their organization:

Recommendation 1.1. Communicate a Vision and Explain How AI Creates Value for the Organization. Executives should communicate how organizational members are expected to engage with AI and how it connects to the firm's strategy. This approach requires executives to develop clarity on their tasks and responsibilities in the AI value creation process and to communicate accordingly.

Siemens' C-level executives consistently highlighted the crucial importance of AI for the company's industry, energy and healthcare businesses, the value potential that lies in the scaling of AI (e.g., for industrial processes) and the need to integrate data science and domain know-how. In 2018, for example, Siemens' chief technology officer stated "We are the leaders when it comes to the industrial application of artificial intelligence and we can offer new services that enable our customers to boost their productivity and efficiency" and recognized that "It is understandable that the increasing involvement of AI in our lives may arouse fears and anxieties and we must take these fears seriously."[34] Communicating an AI vision provides orientation to organizational members and guides their decision-making on prioritizing AI initiatives, use cases and the scaling of the AI portfolio. Ultimately, the leadership's responsibility is to serve as a role model and create trust.

Recommendation 1.2. Promote Communication about AI at all Organizational Levels to Build Trust. Driving AI democratization requires dialogue between AI stakeholders, such as business and IT managers, domain experts (including factory-floor workers), and customers and suppliers to address the AI adoption challenges we have identified. Moreover, the dialogue between organizational members must go beyond their own roles (e.g., domain experts, data scientists or IT specialists). By widening the scope of the dialogue, employees can learn and exchange ideas about AI initiatives and use cases, as well as the experiences and skills that each group can contribute to the development of AI.

The Siemens use cases provide numerous examples of how experts speak about their expectations for increasing acceptance of probabilistic AI outcomes or how to overcome limitations due to AI's black-box nature (e.g., clinicians in the healthcare use case and process experts in the manufacturing examples). Siemens also co-created a shared understanding of AI through prototype development in the AI Lab.

Lesson 2: Enable the Sustainable Exploration and Realization of AI Value Potential

AI only matters for a business if it creates customer value. Democratization can serve as a value driver for AI because the exploration and realization of valuable AI potential are rooted in deep domain and problem knowledge and in involving domain experts and data scientists in the collaborative exploration of data. The need to focus on the customer value created by AI can be easily forgotten in the AI hype. We provide three recommendations for executives to ensure that democratization becomes a value driver for AI.

Recommendation 2.1. Engage Domain Experts Deeply in AI-Based Value Generation to Capture Relevant Business Opportunities. Because domain knowledge is a key ingredient in the effective design of AI tasks and their integration into the business, domain experts have a decisive voice and should contribute to AI-based value generation at all implementation stages. Executives can make AI more relevant,

34 Busch, R., op. cit., January 21, 2019.

appealing and broadly available within their organizations by providing collaboration structures that help to integrate domain and data science expertise. For example, Siemens established cross-functional teams involving domain and data science experts, and their collaborative generation of use case ideas, supported by data and self-service tools, drove the effective design of AI tasks and their integration into products and business processes.

At Siemens' Amberg manufacturing plant, for example, domain and process experts used data and AI self-service tools to prepare AI use cases on their own and were then supported by data scientists in the AI modeling. Hence, instead of viewing AI as an exclusive technology available to only a few, executives should seek to lower barriers for individuals or teams to engage with AI to ensure that AI tasks will solve important and valuable business problems and opportunities.

Recommendation 2.2. Create a Breeding Ground for Exploring Data Value and Generating AI Use Cases and Realizing them. The inseparable link between data and the realization of value-creating AI requires the close collaboration of data scientists and domain experts. To leverage learning and adaptive AI systems, Siemens' democratization actions focused on exploring training data, understanding data and identifying features (e.g., for building hypotheses and AI models). Actions also included the ongoing acquisition of training data to ensure and improve system performance, even during deployment. Executives should ensure that dialogue between domain experts and data scientists takes place "at eye level" so that each group can contribute, based on their different backgrounds and perspectives. However, executives should be aware that because of the inherent culture of experimentation, these collaborations often do not proceed in a linear fashion and do not necessarily lead to concrete, predictable or tangible outcomes.[35] Thus, executives who seek to advance AI democratization should provide sufficient freedom and support for the exploratory nature of such activities.

Recommendation 2.3. Adopt a Value-Oriented Perspective on AI Aligned with the Business Strategy, Corporate Structure and Culture. We recommend that managers and executives focus their efforts on realizing AI applications that leverage the key domain knowledge of their organization and those whose value generation fits well with the organization's business and cultural context. To realize this value generation, organizations need to ensure that end users can handle probabilistic AI outcomes and tolerate the opacity of AI systems.

For example, instead of using its traditional investment strategy (investing in a second deterministic x-ray system), Siemens' Amberg plant management invested in an AI-enabled quality control system. A new decision-making process was established, which took account of the AI system's probabilistic outcomes (only parts with a very low likelihood of failure were not processed through the x-ray quality control system). In the healthcare use case, Siemens Healthineers' AI Companion offered a clear value proposition to radiologists and, at the same time, was designed to take account of the doubts, fears and concerns of clinicians evoked by potential AI opacity (e.g., the system workflow was designed to not independently make any health-related decisions).

The Siemens use cases revealed how AI democratization drives user acceptance of probabilistic AI outcomes. Democratization also proactively addresses AI opacity by involving experts, users and customers early in AI system development to identify and mitigate critical issues related to probabilistic AI outcomes and to understand users' concerns about the transparency of AI applications and their needs for explanations of how the applications make decisions.

Lesson 3: Ensure Efficient Provisioning and Scalability of AI

Long-term success requires that AI applications can be scaled up. Our analysis suggests that AI democratization generates cost advantages when organizations ensure the efficient provisioning and scalability of AI through standardized processes and technology

35 Note that the exploratory character mentioned here is driven by the dual role of data in AI systems (data is used for AI learning as well as for input to AI operation). Hence, developing AI applications differs from traditional software engineering, in which collaborative activities between domain experts and software engineers would typically be intended to elicit user requirements for programming software or for designing interfaces.

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infrastructures. The inherent risk of focusing solely on value creation is that every problem is seen as a "one of a kind." This approach might work in the early stages of AI adoption but detracts from the longer-term benefits of scale economies and learning curve effects.

Analysis of the Siemens use cases revealed that securing the controlled and efficient operation of AI presented new challenges in an area where CIOs can play to their strengths. CIOs can leverage key capabilities of the IT organization to provide data and AI infrastructures and to ensure that corporate-wide initiatives, such as AI tools and learning initiatives, are smoothly and broadly made accessible within the organization. At Siemens, and for many other organizations, long-term AI success is built at scale. The Siemens use cases demonstrate that businesses, whether small or large, can deploy AI in a broad and profitable manner. We provide three recommendations for executives to ensure that democratization provides a cost advantage for AI.

Recommendation 3.1. Encourage Learning about AI Technology for Different Levels of AI Literacy and Facilitate AI Knowledge Transfer. Organizational members, including leaders, managers and employees, are often unfamiliar with the unique characteristics and requirements of AI or how they can apply AI to tasks in their context. Hence, when democratizing AI, executives should establish learning opportunities to make AI relevant, appealing and available at scale in a cost-efficient manner. For example, Siemens' IT organization launched the AI Academy specifically to encourage IT professionals' upskilling and further build Siemens' AI knowledge. Because AI democratization involves organizational members with different roles and experiences, educational initiatives should be tailored to the needs of targeted roles, including their learning objectives and learning paths.

Executives should also facilitate knowledge transfer about successful AI applications to stimulate the scaling of AI across the organization. Siemens facilitated AI knowledge transfer by disseminating best practices and showcases from the Amberg plant to its wider manufacturing network in order to stimulate and advance the scaling of AI at similar manufacturing plants.

Recommendation 3.2. Establish Data and AI Infrastructures to Enable Efficient Operation and Scaling of AI. To ensure the efficient upscaling of AI prototypes into productive applications and their roll-out at scale for a wider range of application contexts, organizations need new standardized tools, frameworks and processes to support and streamline, for example, data acquisition, data federation, data handling, and model (re)training and deployment. To realize the healthcare AI Companion and the manufacturing AI use cases, Siemens carefully selected data and AI infrastructures. These infrastructures were crucial for Siemens' capability to scale AI efficiently—for example, by enabling the integration of externally sourced training data or the transfer of AI models across Siemens' manufacturing network.

We recommend that executives, and particularly CIOs, carefully monitor the developments and AI outcomes generated in business functions and consider, from the start of their AI journeys, how infrastructures can support AI scaling. Establishing data and AI infrastructures not only requires new tools but also encompasses security needs and subsequent future vendor management—areas where the IT organization can contribute substantially to AI democratization.

Recommendation 3.3. Focus on Cost-Efficient Provisioning of AI Applications Rather than Technological Perfection. Valuable AI applications are rarely planned and implemented using the waterfall development model. Instead, as the Siemens use cases suggest, they are collaboratively crafted by competent experts moving iteratively and exploratively from idea generation to implementation and, potentially, the successful scaling into productive AI applications. AI democratization ensures the involvement of diverse experts and thus facilitates a risk-controlled, gradual development of AI that is supported and complemented by a proactive dialogue on the limitations of AI's predictions.

The explorative nature, data dependency and probabilistic outcomes of AI systems represent challenges for executives' decision-making—particularly regarding investment decisions—because the outcomes are less foreseeable than traditional, deterministic software applications. Moreover, the more explorative approach allows organizations to gradually and cost-efficiently address the challenges associated with probabilistic outcomes and AI's opacity by identifying and efficiently managing AI risks, and to explore ways to deal with AI's inscrutability and opacity.

Executives should ensure that the core needs at every AI development stage are supported in a cost-efficient manner and be aware that each succeeding stage tends to become more cost-intensive (due to, for example, the increasing requirements for training data, the potential need for federated learning and the need to ensure that AI applications comply with regulatory requirements). For example, Siemens' corporate initiatives, such as the AI Lab and AI Academy, as well as its venturing unit, enabled AI potential to be explored and shaped at early stages in a highly cost-efficient manner. However, the later development and implementation of the healthcare and manufacturing AI use cases described in this article required relatively higher investments because of their complexity and AI-specific characteristics.

Concluding Comments

Organizations increasingly seek to reap the value promise of AI but struggle to progress their efforts beyond prototypes and individual use cases. A root cause of this issue is that generating value from AI challenges extant organizational practices and routines. The vast amounts of data needed for algorithmic training, the novel forms of interdisciplinary teamwork and using probabilistic outcomes to perform specific tasks do not always sit comfortably with traditional organizational structures and norms.

In this article, we have described how Siemens leveraged AI democratization to identify, realize and scale AI use cases by integrating the unique skills of domain experts, data scientists and IT professionals. The AI democratization process at Siemens evolved through three stages that developed the company's organizational capability and effectively addressed the challenges of adopting AI technologies. Siemens' AI democratization process was not driven by a data science or IT elite but relied on tools and initiatives that leveraged the intelligence and experience available within the organization and its business ecosystems.

Based on our analysis of the Siemens use cases, we have identified three lessons, from which we have derived eight recommended AI democratizing actions for executives. Following these recommendations will ensure that:

- Executives promote and engage in dialogue about the opportunities and risks of AI while proactively positioning their organization for trustworthy, responsible and professional use of AI.
- AI will be deployed to generate value by solving relevant customer and business problems, thereby focusing the company's efforts on the real-world business context.
- Executives, and particularly CIOs, focus on long-term success with AI that is based on scaling valuable applications efficiently within the organization's business domain.

Viewing AI democratization from a value-cost perspective highlights why organizations should build their AI capability in tangible terms so they can address the real-world business challenges they face. Democratizing AI will enable executives and senior leaders to balance the costs and risks associated with exploring the potential of AI to generate value both for their organizations and their customers.

Appendix: Research Methodology

The research for this article is based on an in-depth study of the evolution of AI democratization at Siemens. We focused on how Siemens identifies, realizes and scales AI use cases and how domain experts, data scientists and IT professionals engage in this process.

We conducted the research in two stages. In the first stage, between December 2018 and September 2019, we carried out an online survey of 180 IT and AI practitioners. Survey participants nominated over 90 AI projects and provided an overview of extant AI initiatives and capabilities. We also conducted 25 interviews with business, AI and analytics leaders, and IT managers to discuss how Siemens organized the collaboration between domain experts, data scientists and IT professionals when introducing AI. The interviewees were recruited from multiple organizational units at Siemens (e.g., Siemens Energy, Digital Industries, Mobility, Healthineers and Corporate Technology, as well as several internal service organizations).[36]

Following an initial analysis of the Stage 1 data, Stage 2 of our research (from December 2019 until May 2021) was designed to gain a deeper understanding of Siemens AI initiatives and selected transformative AI applications. More specifically, our focus shifted from AI in Siemens to the process that was used to achieve AI democratization at Siemens. During this stage, we collected and analyzed extensive materials from secondary sources, such as annual reports, shareholder presentations, interviews published on websites and detailed information about the AI applications we studied in depth. For example, for the use cases selected for this article (two at Siemens' manufacturing plant in Amberg and Siemens Healthineers' AI Companion), we scrutinized interviews, presentations and publications that provided technical details about these AI applications.

Because case studies are particularly useful for understanding the context and emergence of a situation (in this case, the emergence of Siemens' AI democratization capability), we consistently iterated between data collection and sensemaking.[37] The first step of our analysis involved an investigation of how Siemens corporate strategy and structure evolved over time and the identification of the most prominent AI initiatives and organizational units associated with it. We then analyzed our interview data and secondary materials using a grounded approach[38] to explore the roles and collaboration of domain experts, data scientists and IT professionals when introducing AI applications. We then further refined our understanding of AI deployment at Siemens until we could comprehensively analyze and describe the evolutionary stages of AI democratization. Finally, we selected suitable AI use cases to illustrate how effective AI democratization works in practice.

36 For details on interviewing techniques in qualitative research, see Myers, M. D. and Newman, M. "The Qualitative Interview in IS Research: Examining the Craft," *Information and Organization* (17:1), December 2007, pp. 2-26.

37 Klein, H. K., and Myers, M. D. "A Set of Principles for Conducting and Evaluating Interpretive Field Studies in Information Systems," *MIS Quarterly* (23:1), March 1999, pp. 67-93.

38 See: 1) Strauss, A. and Corbin, J. M. *Grounded Theory in Practice*, SAGE Publications, 1997; and 2) Corbin, J. and Strauss, A. "Grounded theory Research: Procedures, Canons, and Evaluative Criteria," *Qualitative Sociology* (13:1), March 1990, pp. 3-21.

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